A Rule-Based Approach for Self-Optimisation in Autonomic EHealth Systems

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***Abstract*—Advances in machine learning techniques in recent years were of great benefit for the detection of diseases/medical conditions in eHealth systems, but only to a limited extend. In fact, while for the detection of some diseases the data mining techniques were performing very well, they still got outperformed by medical experts in about half of the tests done. In this paper, we propose a hybrid approach, which will use a rule-based system on top of the machine learning techniques in order to optimise the results of conflict handling. The goal is to insert the knowledge from medical experts in order to optimise the results given by the classification techniques. Possible positive and negative effects will be discussed.**

***Index Terms*—Self-optimisation; Rule-based Systems; Sensor Mediation.**

I. Introduction

Autonomic computing was introduced in 2001 by IBM [1], in order to reduce the need for human involvement in complex computing systems. A few years later, a clearer definition of an autonomic system was developed [2][3]. Autonomic computing is the idea for a system to manage itself and to minimise human intervention. The goals and objectives of the system are ensured by a processing cycle, the MAPE loop, which stands for monitoring, analysing, planning and execution. Also, in order to be classified as an autonomic system, a system needs to exhibit at least the following self-properties, also called self-* properties: self-configuration, self-healing, self-optimisation and self-protection.

In this paper we are going to focus on the self-optimisation property. Optimisation means "an act, process, or methodology of making something (such as a design, system, or decision) as fully perfect, functional, or effective as possible" [4] In our case, we will propose a rule-based system combined with machine learning techniques in order to optimise the decisions taken by the system. We will discuss the application of such a system in the context of eHealth systems.

EHealth systems took advantage of advances in sensor technology, which allowed for more comfortable wearable devices and opened new possibilities for new types of eHealth systems [5][6]. A patient can be monitored constantly at home in a non-invasive way, be it during his rehabilitation process [7] or to detect more elusive conditions that occur only in specific situations. There exist many different systems that have been developed to address these issues. One of these systems is the advanced care and alert portable telemedical monitor (AMON), which is capable of measuring an electrocardiogram (ECG), blood oxygen saturation, blood pressure and skin temperature and has integrated software for the real-time processing of the measured health parameters [5]. Another system that was developed is HeartToGo, which can continuously monitor and analyse an ECG in real time in order to detect cardiovascular diseases [6]. And, finally, LifeGuard [8] is a monitoring system, which is capable of measuring ECG, the respiration rate, the blood oxygen saturation, the skin temperature, the heart rate, the blood pressure and body movement. A more recent application uses Bluetooth in order to connect an Android-based mobile device to connect to a Shimmer sensor node for arrhythmia detection [9].

In this document we are going to discuss the usage of our system in a medical context, however it could be used in any context by adapting the machine learning algorithms and the set of rules. We propose a rule-based system that uses the results of machine learning algorithms in order to optimise the final decision. The goal of the rule-based system is to improve conflict resolution in a medical context resulting from the classification of data coming from different sensors. The system has a dynamic set of rules that can be adapted by the system itself. This means that, depending on the situation, new rules can be added to or removed from the system.

The rest of this paper is structured as follows: The next section shows recent related work that has been done with regards to eHealth systems. In Section III, we will propose our rule-based model and in Section IV we will describe what advantages and disadvantages this system could bring in the context of an eHealth system. Finally, in Section V and VI, we will conclude and discuss future work.

II. Related work

In this section, we will list and describe recent eHealth systems. A very recent healthcare system is shown in [10]. The system has a total of 8 different sensors. However, the main focus of the study was to improve the energy consumption of the whole system and not the classification based on data from different sensors. In [11] and [12] an accelerometer sensor is used in order to help patients with their rehabilitation after a stroke.

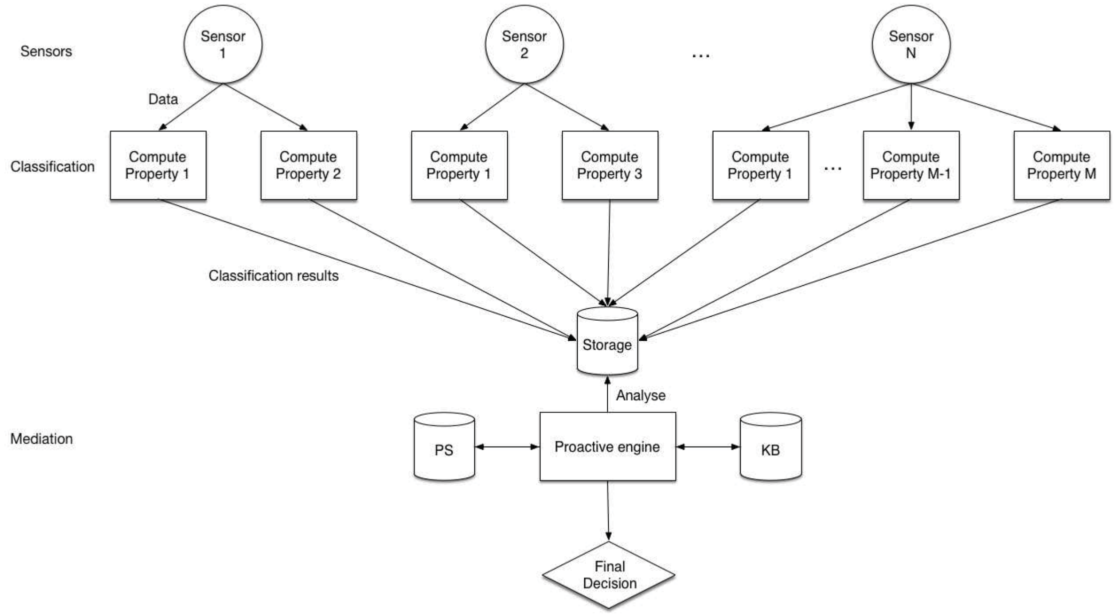

Fig. 1: General structure of the system

These systems all have in common that they do not use the data from the different sensors together in order to improve the diagnosis. In fact, a recent survey and analysis of existing healthcare systems and applications, by Tsakalakis [13], showed that the current systems are missing the appropriate level of decision support and clinical evaluation. For example, in [14], the authors concentrate on ECG data in order to detect cardiovascular diseases. Another similar approach in order to detect pulse loss based on blood pressure data is presented in [15]. A little bit more sophisticated approach is described in [16] in which the authors not only use an ECG sensor but also an Electroencephalogram (EEG) in order to measure brain activity and an Electrogastrogram (EGG), which records the electrical signals of the muscles in the stomach. However, while they use multiple sensors, the diagnosis is done based on data from individual sensors. This means that if for example a sensor detects a problem, the system will alert the patients/doctors without considering the results of the analysis from other sensors. This can lead to false decisions taken if the data was for example influenced by an external source.

In order to overcome some of these limitations, the authors in [17] proposed a multi-tier hierarchy that uses data from multiple sensors in combination with machine learning methods for disease recognition. Another eHealth system uses data fusion methods in order to aggregate data coming from different sensors and other sources like social network feeds[18]. Both approaches allow for small optimisations for the decisions taken.

In [19] the authors use an expert model to do the classification and showed that adding an expert model helped to improve the classification results of epilepsy detection in comparison to a standalone neural-network model. In our system, we want to use a rule-based system in addition to machine learning methods to improve the accuracy of the diagnosis of an eHealth system.

III. A RULE-BASED APPROACH

A rule-based proactive engine was developed recently for different platforms (Windows, Android and iOS). Conceptually, the rules running on the engine [20] can be regrouped into scenarios [21] with each scenario regrouping rules that achieve a common goal.

A Proactive Scenario is the high-level representation of a set of Proactive Rules that is meant to be executed on the Proactive Engine. It describes a situation and a set of actions to be taken in case some conditions are met [22]. For example, in the case of an eHealth system there could be different scenarios (and thus a set of rules) for each type of disease or medical condition that should be detected. The proactive system gives the possibility to disable or enable entire scenarios, thus reducing the number of rules that have to be processed, and enabling the system to be tailored to a specific patient in the case of an eHealth system.

Rules consist of 5 different parts: data acquisition, activation guards, conditions, actions and rule generation and are executed periodically. Both, activation guards and conditions, have to be satisfied in order for a rule to execute its actions. The activation guards are the triggers for a rule to consider taking actions while the conditions are the permissions of a rule. In order to decide, which rules can execute, all rules whose activation conditions are met also have to have the necessary permissions. The list of rules is executed every X seconds where X is a timestamp that can be changed by the system.

In Figure 1, the general structure of the system is shown [23]. Data from different sensors is sent to classification modules, each of which will analyse the data from a single sensor and

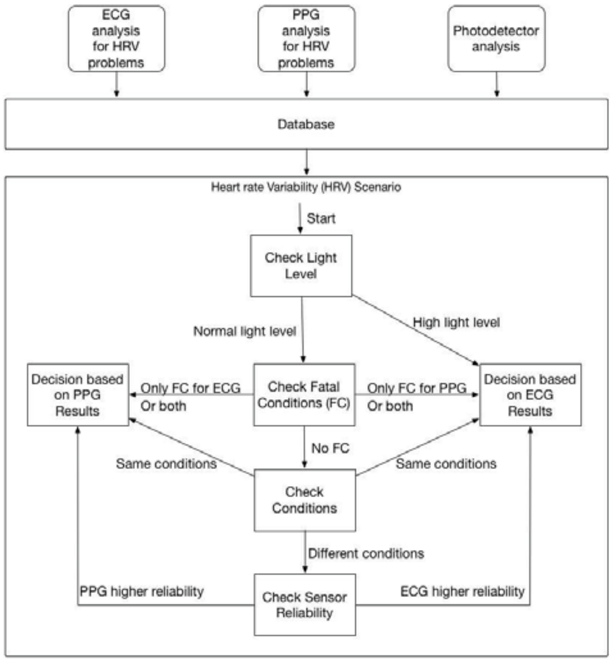

Fig. 2: Heart rate variability scenario

do the classification for a single property. the results are then relayed to the rule-based system in order to aggregate and optimise the results of the final decision. To note here is that the schema presented is as general as possible. In real case scenarios some sensors could be of the same type, data of sensors of different types could be analysed in order to detect the same property, etc.

IV. Self-optimisation scenarios in a medical context

It is important to optimise decisions in a medical context. For the monitoring of patients at home, false positives might be as bad as false negatives as a patient might get annoyed by the false notification he is getting and not use the monitoring device anymore. In this section we are first going to explain the small example of a scenario shown in Figure 2.

The scenario is going to optimise the decision taken for a heart rate variability (HRV) detection with the help of the results of 3 analysis modules: the HRV analysis for an electrocardiogram (ECG), the HRV analysis for a photoplethysmogram (PPG), and the analysis of the photo-detectors to know the current light level. The first rule of the scenario will check the light level and trigger the correct subsequent rules based on the results. As PPGs can be quite susceptible to external light sources, it is safer to ignore the results from that sensor in case of a high light level and just make a decision based on the results from the ECG sensor.

In the case the light level is normal, a rule checks if the sensors detected any fatal conditions (so whether the analysis modules think that the patient is dead). If only one of the 2 sensors think that there is a fatal condition, the results from the other sensor are taken into account to make a decision. If none of the sensors detect any fatal problem, the results from both analysis modules are checked again. If they yield different results, the sensor with the best reliability gets the priority.

Using a rule-based approach in a medical context can have different advantages and disadvantages. We will discuss some of them in the rest of this section, starting with the advantages:

- A manageable way to insert the experience and intuition of medical experts into the system.
  Doctors sometimes have a specific way to decide what do if the results of the tests done are ambiguous. Inserting this knowledge into the system can mean an improvement of the quality of the decisions taken.
- Scenarios can be easily adapted to patients.
  As the proactive engine allows to select the scenarios that should run, only the necessary scenarios can be activated for a given patient. This is useful, as for a specific patient, not every disease or medical condition should or has to be detected. Additionally, scenarios can also take individual patients general information into account for further improving the decisions taken. For example, in the case of a darker skinned patient, it might be wise to ignore the results of analysis done on data from a PPG sensor, as PPG sensors are more and more unreliable the darker the skin of the patient because the technology is using light in order to check the dilatation of blood vessels.

Now we will discuss possible disadvantages of the system in the case of an eHealth application:

Firstly, it can be difficult to collect knowledge from medical experts. This is the case mainly because of 2 reasons.

1) In some cases it might actually be not very easy to convert the knowledge of the expert into rules that will improve the decisions taken by the system.
2) A second reason is the human factor. As there is a large number of diseases/medical conditions that could be detected by the system, there will be a large number of doctors that will need to contribute in order to improve the system. The combination of managing a large number of experts and, in some cases, a reluctance and skepticism from the side of the experts towards the project can present a challenge.

Another important point is the responsiveness of the system(rules are executed every X seconds). While X can be very low we consider and differentiate between a few different cases in order to identify potential drawbacks:

1) Rehabilitation
   In the case the system is used by a rehabilitation patient, the main goal is to guide the patient through his exercise sessions. This includes reminding him to exercise, telling him to increase the intensity of his current exercise session or to reduce the intensity. For these tasks a few seconds between rule executions do not make a huge difference. Another task of a rehabilitation system is to detect if the patient has any critical conditions during

one of his exercise sessions. This task is time critical and a few seconds could make a difference, although the main deciding factor whether the patient survives will be how fast the emergency services can get to him.

2) Monitoring/detection of diseases The general monitoring of a patient, mainly for the detection of elusive diseases is not time critical for the rule-based system, meaning that as the analysis modules analyse the data in real time and save their results to the database, a few seconds between rule executions do not affect the performance of the system in a negative way.

Finally, the power consumption of the wearable devices is an important factor to consider as well. The wearable devices that are used for monitoring patients at home are reliant on their batteries in order to function. A high power consumption of the system thus could make it unusable in a real life scenario. However, initial tests have shown that the effects of the rule-based system on the battery and the performance of the device are negligible [24].

V. Conclusion and future work

In this paper we proposed a structure for a rule-based autonomic system. With the help of this rule-based system we want to optimise the decisions taken by the system based on classification results from different sensors. We showed a possible scenario on how the rule-based system could be used to improve the decisions taken and we discussed possible advantages and disadvantages that such a system brings in the context of an eHealth application.

For the future we plan to design, implement and test the rule-based scenarios on real eHealth devices. These tests will include experimentation with different machine learning algorithms, in order to see which ones are best suited for eHealth applications. Furthermore, we plan to add learning mechanisms to the system which will dynamically change the set of rules and/or parameters of the rules depending on the results or consequences of past decisions. This way the system does not only adapt the set of rules based on the input of the sensors but also based on its own actions, which could allow for an even better optimisation of the decisions taken.

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